

COMPUTERIZED PLANT COMMUNITY CLASSIFICATION: AN APPLICATION OF FUZZY LOGIC

L. B. Nadeau, C. Li, and I. G. W. Corns

Northern Forestry Centre
Information Report NOR-X-384



Natural Resources
Canada
Canadian Forest
Service

Ressources naturelles
Canada
Service canadien
des forêts

Canada

The Canadian Forest Service's Northern Forestry Centre is responsible for fulfilling the federal role in forestry research and technology transfer in Alberta, Saskatchewan, Manitoba, Nunavut, and the Northwest Territories. The main objective is research in support of improved forest management for the economic, social, and environmental benefit of all Canadians.

The Northern Forestry Centre is one of five centers of the Canadian Forest Service, which has its headquarters in Ottawa, Ontario.

Le Service canadien des forêts, Centre de foresterie du Nord, représente le gouvernement fédéral en Alberta, en Saskatchewan, au Manitoba, au Nunavut et dans les Territoires du Nord-Ouest en ce qui a trait aux recherches forestières et au transfert de technologie. Cet organisme s'intéresse surtout à la recherche en vue d'améliorer l'aménagement forestier afin que tous les Canadiens puissent en profiter aux points de vue économique, social et environnemental.

Le Centre de foresterie du Nord constitue l'un des cinq établissements du Service canadien des forêts, dont l'administration centrale est à Ottawa (Ontario).

Cover photograph courtesy of Xinhai Li, Canadian Forest Service.

**COMPUTERIZED PLANT
COMMUNITY CLASSIFICATION:
AN APPLICATION OF FUZZY LOGIC**

L.B. Nadeau¹, C. Li, and I.G.W. Corns

INFORMATION REPORT NOR-X-384

Canadian Forest Service
Northern Forestry Centre

2002

¹ Northern Alberta Institute of Technology, Edmonton, Alberta

© Her Majesty the Queen in Right of Canada, 2002

Catalogue No. Fo46-12/384E

ISBN 0-662-32867-1

ISSN 0704-7673

This publication is available at no charge from:

Natural Resources Canada
Canadian Forest Service
Northern Forestry Centre
5320 - 122 Street
Edmonton, Alberta T6H 3S5

A microfiche edition of this publication may be purchased from:

Micromedia Ltd.
240 Catherine Street, Suite 305
Ottawa, Ontario K2P 2G8



NATIONAL LIBRARY OF CANADA CATALOGUING IN PUBLICATION DATA

Nadeau, Léonie Bernadette

Computerized plant community classification : an application of fuzzy logic

(Information report ; NOR-X-384)

Includes bibliographical references.

ISBN 0-662-32867-1

Cat. no. Fo46-12/384E

1. Biotic communities - Alberta - Classification - Computer programs.
2. Vegetation classification - Alberta -- Computer programs.
3. Botany - Alberta - Classification - Computer programs.
4. Fuzzy logic.
 - I. Li, C. (Chao)
 - II. Corns, I.G.W. (Ian George William)
 - III. Northern Forestry Centre (Canada)
 - IV Series : Information report (Northern Forestry Centre (Canada))

QH106.N32 2002

577.8'2'012

C2002-980235-0



This report has been printed on Canadian recycled paper.

DEDICATION

This report is dedicated to Dr. Ian G.W. Corns, who helped initiate this project in summer 2001. Dr. Corns's ideas and established research on ecosite classification in Alberta formed the foundation for this project. He will be deeply missed.

Nadeau, L.B.; Li, C.; Corns, I.G.W. 2002. Computerized plant community classification: an application of fuzzy logic. Nat. Resour. Can., Can. For. Serv., North. For. Cent., Edmonton, AB. Inf. Rep. NOR-X-384

ABSTRACT

Decisions for classifying a vegetation plot are based on expertise and can thus be subjective, with users having to judge the relative importance of overlapping biotic and abiotic components. Fuzzy logic can be used to incorporate experts' knowledge of ecosystems into computer programs. A classification of the forested portion of the Montane subregion of west-central Alberta by plant community type (a level more detailed than ecosite) was translated into a simple fuzzy logic program. The program was tested, by means of a fuzzy logic software package, FuzzyTECH, on 147 Ecological Site Information System plots compiled by Alberta Environment. The computer classification was identical with the experts' classification for 80% of the plots, and where differences occurred it was easy to identify the reasons for the discrepancies. Anyone who can identify plant species could be sent to the field to obtain the information needed for this type of computer analysis and classification.

RÉSUMÉ

Dans la classification d'une parcelle de végétation, les décisions sont prises par des experts; elles peuvent donc être subjectives dans la mesure où les usagers doivent juger de l'importance relative de composantes biotiques et abiotiques entremêlées. On peut faire appel à la logique floue pour incorporer dans des programmes informatiques les connaissances d'experts en écosystèmes. La classification d'une zone forestière de la sous-région montagnarde du centre-ouest de l'Alberta par type de phytocénose (un niveau plus détaillé que l'écosite) a été traduite en un programme simple à logique floue. Le programme a été testé au moyen d'un logiciel à logique floue, FuzzyTECH, sur 147 parcelles du Système d'information sur les sites écologiques répertoriées par le ministère de l'Environnement de l'Alberta. La classification informatisée s'est révélée identique à celle des experts pour 80 % des parcelles, et là où on observait des écarts, il était facile d'en trouver les raisons. Quiconque est capable d'identifier les espèces de plantes pourrait aller recueillir sur le terrain les données nécessaires à ce type d'analyse et de classification informatisées.

CONTENTS

INTRODUCTION	1
BACKGROUND	2
MATERIALS AND METHODS	2
Data Source and Preparation	2
Membership Functions and Translation of Rules	3
Description of Fuzzy Logic Algorithm	7
Fuzzification	7
Rules	7
Defuzzification	7
Program Calibration	8
RESULTS AND DISCUSSION	8
Advantages of Fuzzy Logic Classification over Keying with Field Guides	10
Advantages and Disadvantages of FuzzyTECH	10
ACKNOWLEDGMENTS	11
LITERATURE CITED	12

TABLES

1. Plant species used in the fuzzy logic program to classify the forested portion of the Montane Natural Subregion of west-central Alberta	3
2. Output table from data collected for one plot from the Montane Natural Subregion of west-central Alberta	6

FIGURES

1. Membership functions of the variable <i>arctuva</i> , which represents percent cover of the species <i>Arctostaphylos uva-ursi</i>	4
2. Membership functions for the output variable <i>Aw_rose_rye</i> , which represents the plant community type aspen/prickly rose/hairy wild rye.	4
3. Structure of a portion of the fuzzy logic system	5

APPENDIXES

1. Description of input variables	13
2. Description of output variables	14
3. Description of intermediate variables	15
4. Rule block for the output variable <i>Aw_rose_rye</i> , which represents the plant community type aspen/prickly rose/hairy wild rye	16
5. Rule block for the intermediate variable <i>wildrye1</i>	18
6. Rule block for the intermediate variable <i>Aw_Pb</i>	22

INTRODUCTION

Conservation and management of biodiversity necessitate the development of nationally and internationally recognized methods for classifying ecological communities, whereby ecosystems are ordered into functional units (Ponomarenko and Alvo 2001). These units would have similar flora and soils that would be expected to respond to changes in the environment in a similar manner (Corns and Annas 1986; Beckingham et al. 1996). In Canada, the government is striving to produce one general classification system, but more than 50 local ecosystem classifications have been created (Ponomarenko and Alvo 2001). Although most of these classifications were produced to meet specific management needs, the lack of consensus also reflects the inherent complexity of ecosystems. Classification depends on decisions as to which biotic or abiotic components are most influential in a given plot. Ecosystem classification experts often have different opinions on the importance and impact of various soil and plant factors, which results in different classification systems.

The use of ecological land classification (ELC) systems is generally considered an important step toward the sustainable management of forested land, because ecosystems with similar characteristics are expected to respond to disturbances in a similar manner. With this in mind, a hierarchical structure, such as the ecozone, ecoprovince, and ecoregion hierarchy defined by the Ecological Stratification Working Group (1995), has been used in ELC systems. One major ELC system exists for Alberta, originally produced by Corns and Annas (1986) and later modified by Beckingham et al. (1996). This particular ELC system has a hierarchical structure of natural region, subregion, ecosite, ecosite phase, and plant community type.

The *Field guide to ecosites of west-central Alberta* (Beckingham et al. 1996) provided a framework based on plant community types of west-central Alberta that complemented the users' knowledge

and facilitated their decisions on a variety of activities in forest resource management; however, ecosite classification in the field guide was still somewhat subjective. This situation was not unique to Alberta. To overcome this type of limitation, attempts have been made throughout Canada to develop computer models for consistent classification of plots.

One computerized knowledge-based ecosystem classification, EcoGen, was developed by the government of British Columbia (Meidinger et al. 2000). It uses geographic and inventory data to map geoclimatic ecosystem classification units of that province. In Ontario, the Northwestern Ontario Forest Ecosystem Classification was translated into a user-friendly program, FEXPERT, by computerization of the essential elements of its key (Payandeh et al. 1995). In Alberta, another computerized ecosystem classification, the Ecological Land Data Acquisition Resource, or ELDAR, which stemmed from the Naia program (Mulder and Corns 1993), was designed to represent the knowledge that a forest ecologist would use to infer a forest ecosystem from geographic, soil, and forest cover attributes. Classification could be done at the ecosite level and subsequently could be linked to a geographic information system (GIS) database for producing maps. However, ELDAR was based on ecosite classification, a broader level than plant community type. Thus, fuzzy logic might be a better alternative for more precise classification of ecosystems. It could be used to computerize essential elements of dichotomous keys for ecosystem classification, as was done in the FEXPERT program, but with the added advantage of fuzzy logic flexibility, and the resulting outputs could be linked to GIS databases to produce maps.

In this report, the application of fuzzy logic technology to ELC data is described. Potential linkage of the data to GIS databases is not covered here.

BACKGROUND

Fuzzy logic technology was developed for applying the fuzzy set theory in addressing practical issues. In simple terms, the "fuzziness" of any measurement can range from absolute precision (in which case the measurement is not fuzzy) to an assessment or opinion based on intuition (in which case the measurement is completely fuzzy).

Although Zadeh was responsible for coining the term "fuzzy" to describe computing methods that approximate reasoning in intelligent systems (Sowell 1998), it was Mamdani (1975) who first applied the concept by developing the first fuzzy logic controller, in this case for a steam engine. With conventional programming, which is based on Boolean logic representing mathematical models, the speed of the steam engine could not be controlled properly, and the engine would overshoot the target speed or would be too sluggish. With fuzzy logic programming, the target speed could be achieved rapidly without overshooting, through automation of decisions that led to reproducible and consistent results (Mamdani 1975). Since then, fuzzy logic programming has been used for appliances, in the automotive industry, and in industrial control systems to save energy and simplify automated tasks (von Altrock 1995). More recently, fuzzy logic has found applications in business and banking, where it is used for selecting customers and identifying trends (von Altrock 1997). The major advantages of fuzzy

logic programming in these situations are that the experience of more than one person can be translated into the program and that large quantities of decisions such as those needed for stock markets, can be made at low cost.

Fuzzy logic was first applied to forest land management by Bare and Mendoza (1988) and to vegetation ecology by Roberts (1989), who later suggested that this approach could be used to classify vegetation succession or responses to disturbance (1996a, 1996b). Individual plots were assigned membership values (i.e., their placement in the range from 0 to 1 on the basis of an assessment) for each community type, which indicated the degree to which the vegetation met the definition of each community type. Vegetation dynamics were represented by changes in membership values with time. Through an expansion of this concept, individual plots could become partial members of more than one plant community type at a given time; it is then up to the human experts, their knowledge computerized by fuzzy logic, to decide to which community type the plot best belongs. This reasoning was applied in this study to determine the plant community types for individual plots, on the basis of the key for plant community classification of the forested portion of the Montane Natural Subregion of west-central Alberta, described in Beckingham et al. (1996, p. 9-8 to 9-10).

MATERIALS AND METHODS

Data Source and Preparation

A data set covering 147 Ecological Site Information System (ESIS) plots was obtained from the Data Management Section of the Resource Data Branch of Alberta Sustainable Resource Development. The data covered soil, parent material, site, plant species, strata, tree measurement, and tree regeneration characteristics. Only the data on moisture and nutrient regimes and 17 plant species

or genera (Table 1) were used for this analysis. Genera rather than species were used in instances when the key by Beckingham et al. (1996, p. 9-8 to 9-10) referred to them.

For 47 of the 147 plots moisture regime had not been identified, and for 144 of the plots, nutrient regime had not been identified. For these plots, values were extrapolated from data for site, soil, and parent material. Moisture regime was extrapolated

from drainage, perviousness, slope, and aspect data, and nutrient regime was extrapolated from soil data, such as pH, Ah thickness, and presence or absence of an organic horizon. Shrub cover was determined by summing all percent cover values for shrub species from among the 17 plant species or genera. The data were then prepared for use in the fuzzy logic classification program. The program, which used the software package FuzzyTECH (Inform Software Corporation 2001), was an adaptation of one of the keys by Beckingham et al. (1996, p. 9-8 to 9-10). The *Field guide to ecosites of west-central Alberta* (Beckingham et al. 1996) was used to develop the classification program. This report focused only on the forested portion of the Montane Natural Subregion of the Rocky Mountain Natural Region of west-central Alberta. Input variables (plant species cover, shrub cover, and moisture and nutrient regimes), output variables (plant community types), and rules were translated from the detailed information given for each of the plant community types.

Table 1. Plant species used in the fuzzy logic program to classify the forested portion of the Montane Natural Subregion of west-central Alberta

Scientific name	Common name
<i>Amelanchier alnifolia</i>	Saskatoon
<i>Arctostaphylos uva-ursi</i>	Bearberry
<i>Cornus stolonifera</i>	Red-osier dogwood
<i>Elymus innovatus</i>	Hairy wild rye
<i>Equisetum</i> spp.	Horsetail
<i>Heracleum lanatum</i>	Cow parsnip
<i>Juniperus</i> spp.	Juniper
<i>Ledum groenlandicum</i>	Labrador tea
<i>Picea glauca</i>	White spruce
<i>Picea mariana</i>	Black spruce
<i>Pinus contorta</i>	Lodgepole pine
<i>Populus balsamifera</i>	Balsam poplar
<i>Populus tremuloides</i>	Trembling aspen
<i>Pseudotsuga menziesii</i>	Douglas-fir
<i>Rosa acicularis</i>	Wild rose
<i>Salix</i> spp.	Willow
<i>Shepherdia canadensis</i>	Canada buffalo-berry

Membership Functions and Translation of Rules

To use a fuzzy logic program, measured values must be translated into words (linguistic variables), and a relationship between the two must be established. This relationship is called a membership function. The process of translating measured values into linguistic variables by means of a membership function is referred to as fuzzification. Four linguistic terms were used to represent cover: very low, low, medium, and high. These terms described the potential fit of percent cover. For example, to translate the real (input) variable *arctuva* (representing *Arctostaphylos uva-ursi* cover) into a linguistic variable (Fig. 1), each of the four linguistic terms was described by a membership function that defined, for any value of the *arctuva* variable, the associated degree of membership in the linguistic term. For example, an *arctuva* cover of 15% is a member of each membership function as follows:

very low,	membership value of 0;
low,	membership value of 0.8;
medium,	membership value of 0.7;
high,	membership value of 0.2.

In a similar way, the output variables, which were plant community types of the forested portion of the Montane Natural Subregion of west-central Alberta, had to be fuzzified. Output variables were translated into linguistic variables with membership functions, as shown in Figure 2 for the output variable *Aw_rose_rye*, representing the plant community type aspen/prickly rose/hairy wild rye. The linguistic terms for output variables were very low, low, medium, high, and very high, and described the potential fit of plot data to plant community types. Intermediate variables, often used for simplifying the program, were also created with linguistic terms.

Appendixes 1, 2, and 3 list details of the input, output, and intermediate variables for this analysis.

With the help of these defined variables, the rules summarized in the field guide were translated by means of if, then expressions. A collection of such linguistic rules for a given output variable (i.e., the

various plant community types) is called a rule block. Appendix 4 presents the rule block for the output variable Aw_rose_rye, which represents the plant community type aspen/prickly rose/hairy

wild rye, and Appendixes 5 and 6 contain rule blocks for the intermediate variables wildrye1 and Aw_Pb, which are used in the Aw_rose_rye rule block.

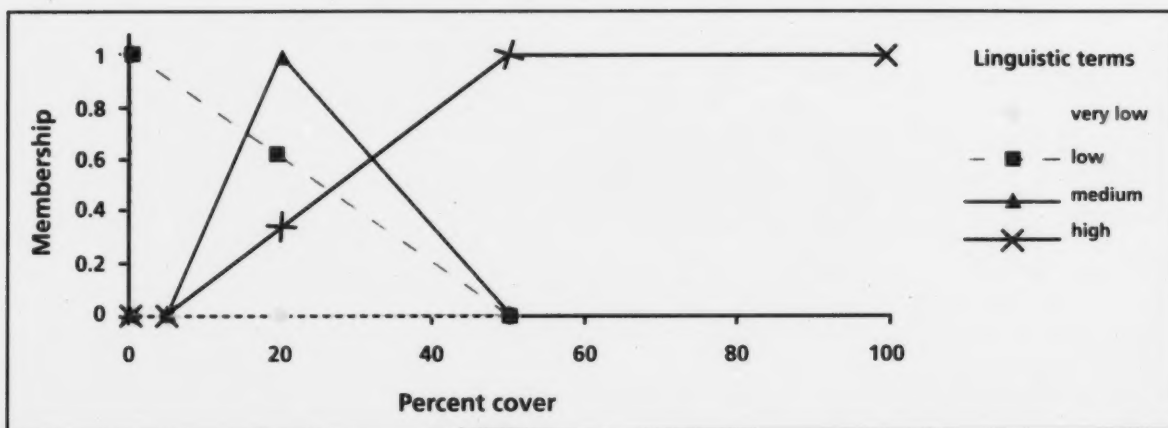


Figure 1. Membership functions of the variable *arctuva*, which represents percent cover of the species *Arctostaphylos uva-ursi*. Any value of the *arctuva* variable has a membership value for each of the four linguistic terms, as indicated by the graph.

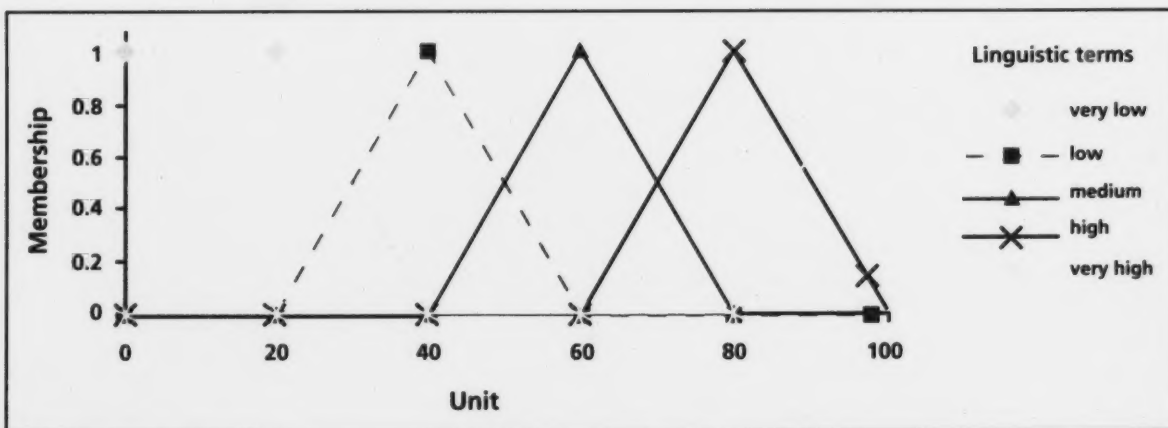


Figure 2. Membership functions for the output variable *Aw_rose_rye*, which represents the plant community type aspen/prickly rose/hairy wild rye. Any unit of the *Aw_rose_rye* variable has a membership value for each of the five linguistic terms, as indicated by the graph.

Finally, after a set of data for one plot has been "fuzzified" and run through the rule blocks, it must then be "defuzzified".

Figure 3 represents examples of the process from fuzzification to defuzzification. The percent cover values for the 17 species or genera (Table 1) and the moisture and nutrient regimes for a plot are fed into the fuzzy logic program as a *.csv file. The information from the plot is then fuzzified by the computer program. The first column of boxes in Figure 3 represents the membership functions defined for each species or genera and moisture and nutrient regimes as shown in Figure 1. The fuzzified information for that plot (i.e., the membership values

for each linguistic term for each species and for the nutrient and moisture regimes) are run through the rule blocks, such as the one presented in Appendix 4. Depending on the membership values of the linguistic terms of the inputs, the computer program assigns linguistic terms to the outputs. These linguistic terms are then defuzzified by means of a defuzzification algorithm (see next section) that uses membership functions such as the ones shown in Figure 2 and illustrated by the third column of boxes in Figure 3. The computer program then assigns a numeric value to each output. The output (i.e., plant community type) with the highest numeric value represents the plant community type that best fits the plot data.

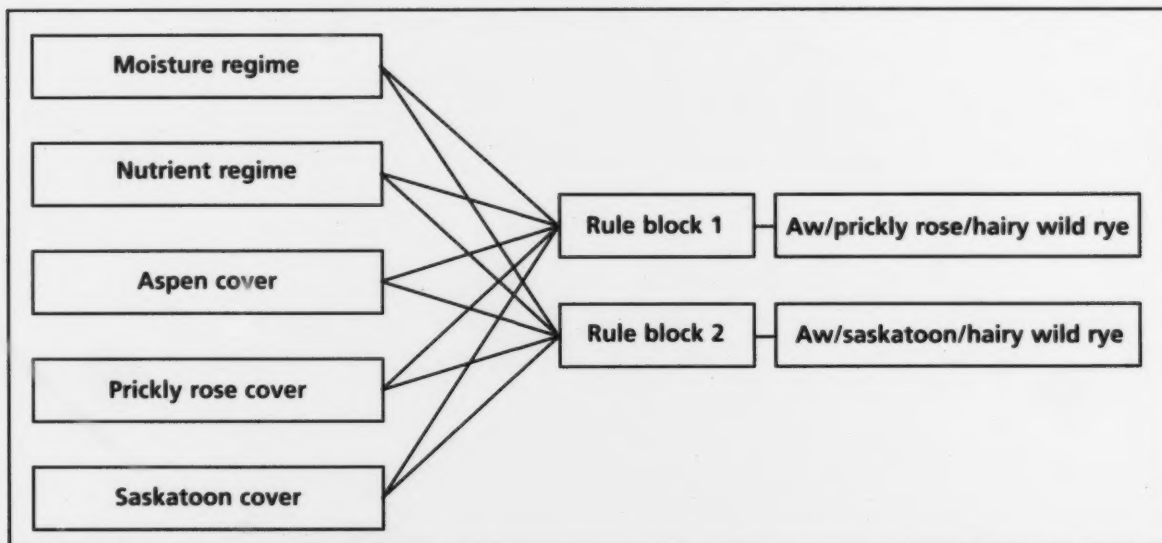


Figure 3. Structure of a portion of the fuzzy logic system. The rule blocks consist of a number of quantitative descriptions of input variables, which take the form of if-then statements. See Appendix 1.

Table 2 represents an example of an output table. The numeric values for percent cover (column 2) were fuzzified, were run through rule blocks, and then were defuzzified into numeric values shown in

the last column of the table. The best fit by far is for the output variable Sw_horsetail, which represents the plant community type Sw/horsetail.

Table 2. Output table from data collected for one plot from the Montane Natural Subregion of west-central Alberta

Input variables		Output variables	
Input name	Percent cover	Output name	Analog value
amelaln	0.00	Aw_bearbuff_rye	9.65
arctuva	0.00	Aw_buff_rye	10.00
betupap	2.00	Aw_rose_rye	8.88
cornsto	1.00	Aw_sask_rye	8.88
elyminn	3.00	AwSwPl_bear_rye	10.40
equispp	61.00	AwSwPl_buff_rye	10.00
heralan	0.00	AwSwPl_rose_rye	9.39
junispp	1.00	Fd_bearbuff_rye	10.00
ledugro	0.00	Fd_buff_rye	9.39
moisture_regime	7.00	Fd_wildrye_fmoss	9.64
nutrient_regime	4.00	PbAw_cowparsnip	9.39
picegla	47.00	PbAw_dogwood	12.69
picemar	0.00	PbAw_horsetail	11.18
pinucon	0.00	PbSw_dogwood	37.77
popubal	6.00	Pl_bearbuff_rye	9.65
poputre	0.00	Pl_buff_rye	9.65
pseumen	0.00	Pl_fmoss	9.13
rosaaci	3.00	Pl_wildrye	9.65
salispp	9.00	Sb_labte_sed_gmo	9.65
shepcan	1.00	Sb_willow_sed_gm	10.00
shrub	15.00	Sw_bearjun_fmoss	10.00
		Sw_fmoss_wfmoss	10.00
		Sw_wildrye_fmoss	10.00
		Sw_willow	66.12
		Sw_buff_rye_fmos	10.00
		Sw_horsetail	97.46

Description of Fuzzy Logic Algorithm

This section described the fuzzy logic algorithm in greater detail for the benefit of those interested in applying this method to other classification systems. As described above, the program used to computerize classification of plant community type required three steps: fuzzification, application of rules, and defuzzification.

Fuzzification

Numeric values for each variable were translated into words (linguistic terms), and membership functions relating the numeric values to these linguistic terms were defined. The input variables were species cover, shrub cover, and moisture and nutrient regimes (see Appendix 1). Four linguistic terms were used to describe species cover (very low, low, medium, and high) and two to describe shrub cover (low and high). Nine linguistic terms were used to describe moisture regime (very xeric, xeric, subxeric, submesic, mesic, subhygric, hygric, subhydric, and hydric) and five to describe nutrient regime (very poor, poor, medium, rich, and very rich). The input variables were fuzzified by manually computing the membership function for each input value. For species and shrub cover, the membership functions were linear, but for moisture and nutrient regimes versus membership bell-shaped distributions were used. With a bell-shaped function, small changes in moisture or nutrient regimes around a given linguistic term (e.g., hydric) would have minimum impact on the membership value of a plant species typical of that linguistic term. Thus, a moisture regime of 7.7 (maximum value 10) would be considered hydric, with a membership much closer to 1.0 than if the function describing that linguistic term had been linear.

The output variables were plant community types of the forested portion of the Montane Natural Subregion of west-central Alberta. The output variables were also fuzzified, and membership functions relating linguistic terms to numeric values were defined. Five linguistic terms were used to describe the "best fit" of each of the plant community types, given a set of environmental conditions and species cover (very low, low, medium, high, and very high) (see Appendix 2).

Rules

If-then rules for processing the fuzzified variables used linguistic variables for input, intermediate, and output variables according to membership functions.

The rules contained the control strategy of the fuzzy logic system. The "if" portion of a rule described the situation for which the rule was designed. The "then" portion described the response of the fuzzy system in this situation. Only the strongest (most true) rules were to be evaluated by the program, so the minimum/maximum operator (MIN/MAX) method was used. Use of the operator type MIN stemmed from the consideration that in this fuzzy logic system more than one rule could be true for a given plot, for example, rule 1 was true AND Rule 2 was true. Use of the operator type MAX implied that the rules were produced alternately: either rule 1 was true OR rule 2 was true OR rule 3 was true, and so on. Only the strongest rule (i.e., the most true) was retained for defuzzification.

The following algorithm describes the MIN/MAX method:

$$\mu = \lambda \cdot \max_{i=1}^m \{\mu_i\} + (1 - \lambda) \cdot \min_{i=1}^m \{\mu_i\}$$

where μ refers to a membership value, i and m refer to units, and λ represents a linear combination of the MAX and MIN operators (Von Altrock 1997).

Defuzzification

Defuzzification is the process of translating linguistic output terms into the numeric values that best represent the fuzzy value of the output term. Of the several possible methods of defuzzification, the best compromise method was used, whereby the most typical value for each linguistic term (i.e., the maximum membership of the respective membership function), was determined. The typical values were weighted proportional to the level to which the action was true, and then the best compromise of the fuzzy logic result was computed.

In the translation of the key of plant community types (Beckingham et al. 1996), input and output

variables were defined and the rule blocks described, as outlined above. From the numeric values obtained by defuzzification, plant community types could be ordered in terms of best fit to the plot data. The two best-fitting plant community types for a given set of plot data were compared with the plant community type chosen by experts. The two best-fitting plant community types were used for the comparison because in some cases the two types had the same or very similar numeric values.

Program Calibration

The fuzzy logic program was adjusted to improve the correlation between the experts' evaluation of the 147 ESIS plots and the program's evaluation of the data. This calibration involved adjustments to membership functions and rule blocks. The linguistic term "very low" was added during the calibration to allow better description of potential cover for each plant species. Use of a plant species cover value of zero, rather than "less than 5%" substantially influenced the classification of plant community types. For the variable *wild_rye*, representing the cover of hairy wild rye, the membership function for the linguistic term "low" was changed to fit better the key from Beckingham et al. (1996, p. 9-8 to 9-10): it had a membership function of 0 at 10% or greater cover, rather than at

50% or greater cover for other species. In addition, some rules were slightly changed and new rules were added as required. For example, if for a plant community type chosen by experts for two plots, the same choices were not made by the computer program (i.e., two plant community types with the best fit), the rule block for that plant community type was reassessed.

Another calibration method consisted of adding plant species to rule blocks, as for the output variable *Aw_rose_rye*, representing the plant community type aspen/prickly rose/hairy wild rye. This plant community type initially had rules pertaining to aspen only; extra rules were added to include balsam poplar as a potential dominant species.

The final calibration affected shrub cover. The ESIS plot data did not include percent shrub cover, so these values were calculated. Many types of calculations for shrub cover were used, from summing the percent cover for the shrub species used in the computer program to summing the percent cover of all shrubs measured in a plot to summing the percent cover of shrubs measured in a plot and subtracting that for dwarf shrubs. In all cases, however, the computer classification of plant community types was similar.

RESULTS AND DISCUSSION

Of 147 plots from Alberta Sustainable Resource Development, the computer classification matched the experts' classification for 118 (80%). Of these 118 plots, 105 (89%) were classified as the same plant community type by both the computer program and the experts, and for 13 (11%) the program's second-best classification matched that of the experts. In the latter cases, the two highest numeric values assigned to the plant community types after defuzzification were so similar that it was decided to consider the top two choices of the computer program as valid.

Where differences occurred between the computer program and the experts' classification, it

was easy to identify the reasons for the discrepancies. Shrub cover, independent of how it was calculated, was a major reason for differences. Shrub cover was calculated from the original data, and these values might have overestimated true shrub cover, because there was no accounting for overlapping shrub cover. Therefore, for 15 of the ESIS plots, the fuzzy logic program generated plant community types within high shrub cover, whereas the experts had specified community types with low shrub cover.

The computer program was not always successful in assigning a best-fit numeric value to plant community types for a set of plot data. In five instances, the numeric values for one set of plot data

were so close that there was a tie between three or more plant community types. In all such cases, none of the numeric output values were greater than 10 (maximum 100). The experts probably used plot characteristics other than the ones provided to the program to classify these plots.

A major challenge in translating keys for classifying plant community type was choosing the proper level of sensitivity or robustness for the program. The linguistic terms had to be robust enough to minimize the impact of 1–3% changes in cover of individual species in a set of plot data. In some instances, however, no calibration would result in a similar classification from both the computer and expert classification. This problem occurred when the experts classified a plant community as a specific type that was difficult to determine from the key. In these instances, some plots with a low percent cover of a given species might be classified by the experts as a plant community that would typically have a high percent cover for that species, if other characteristics fitted the description of that particular plant community type. For four plots, the experts deviated from the dichotomous key of Beckingham et al. (1996) in classifying ESIS plot data for the Montane Natural Subregion. For example, a plot with a mesic moisture regime, a medium nutrient regime, white spruce (*Picea glauca*) cover of 28%, balsam poplar (*Populus balsamifera*) cover of 1% and no lodgepole pine (*Pinus contorta*) cover was classified as Aw_Sw_Pl/Canada buffalo-berry/hairy wild rye rather than Aw/Canada buffalo-berry/hairy wild rye. Experts have reported that they have not always been successful in using the Beckingham et al. (1996) keys for classifying plant community types, but that these keys did point in the right direction.

Finally, discrepancies were caused by moisture regime. Four plots classified by the experts as having high moisture regimes were also classified by these experts as plant community types typical of drier environment; in one plot, the opposite occurred. Calibrating the computer program to deal with these discrepancies enabled the authors to solve the problems for some plots, but similar problems then appeared for other plots.

The correlation between the computer program's classification and that of the experts compared favorably with what was obtained with ELDAR: the Alberta Research Council has reported that for at least 75% of the plots ELDAR and experts generated the same classification at the ecosite level. However, the input variables for the fuzzy logic program were different from the ones used by ELDAR, as the fuzzy logic program focused on classifying plant community types, not ecosites. The fuzzy logic program closely followed the dichotomous key of Beckingham et al. (1996) for the Montane Natural Subregion, and used mainly understory plant cover rather than geographic characteristics, such as landform, as input. The geographic and soil attributes of a plot are generally more reliable than plant cover for identifying ecosystems. Plant species and their cover would be more prone to variation because of seed dissemination by wind and animals. If geographic attributes had been used in the fuzzy logic program in addition to species data, the computer classification would probably have fitted even better with experts' choices for the ESIS plots. The flexibility of the fuzzy logic program means that it can be easily modified, and the input variables could be expanded to include the input variables used for the ELDAR analysis. Furthermore, a fuzzy logic program could be created to classify ecosites only.

For both input and output variables, the linguistic terms were subjective. Inclusion of more terms would have made the rule blocks more sensitive. Similarly, including the degree of support used to weight each rule would have made the program more sensitive. For example, in the definition of the rules, hairy wild rye might be expected to have a low cover under subhygric conditions; "low" as defined by our linguistic variable wild_rye might be too high, but "very low" might be too low. Adding a new linguistic term such as "low/very low" for subhygric conditions or changing the degree of support for low from 1 to 0.5 might have made the program more sensitive.

For processing the rule blocks, operator types other than the MIN/MAX operator could have been used. Some operator types include a degree of

compensation that imitates the human decision process more accurately than the MIN/MAX operator; however, they have the disadvantage of reducing computation speed.

For defuzzification, the best compromise method was used, which gave the program more freedom and did not limit our results to the definitions of the linguistic terms for each variable. Other defuzzification methods were not as flexible. For example, with the most plausible result method, the typical value of a linguistic term that is most valid is computed. The data was reanalyzed using this method, and the computer program choices matched those of the experts for 81 (55%) of the 147 ESIS plots.

Fuzzy logic is a simple way to translate experts' knowledge into computer programs. This program was flexible and could be modified easily to fit the opinions of experts through adjustment of membership values, rule blocks, degree of support for each rule, operator type, and defuzzification method.

Ecosystem classification, such as that produced by our fuzzy logic program, provides a framework to describe the nature of ecosystems, but an ecosystem map shows the actual distribution of these ecosystems. Ecosystem mapping is considered a necessary tool in the development of management plans. Through remote sensing, GIS, and fuzzy logic programs, it should be possible to produce maps predicting the biotic and abiotic attributes of polygons as well as ecosystem classifications.

Advantages of Fuzzy Logic Classification Over Keying with Field Guides

Fuzzy logic has three main advantages over keying with field guides. First, anyone with a little experience in ecosite classification can gather the field information needed as input variables for the program (e.g., plant species cover and moisture and nutrient regimes). Numeric values generated by the fuzzy logic program can then be used to classify each plot. Since the rules are the same for each plot, the classification is based on the same expert's judgment each time, which removes personal bias.

Second, fuzzy logic programs can be user friendly and fast. Data for a set of plots can be run simultaneously. For example, the data from the 147 plots used here were analyzed in less than 1 second by a computer with a processor speed of 233 MHz and 64 MB of RAM.

Third, all of the potential plant community types, with their numeric values, appear in the output table for a plot. This information helps in determining how well a plot fits the description of a particular plant community type, and in identifying characteristics considered by the program as dominant for that particular plot (on the basis of the set of rules that was entered).

It can be a challenge for forest managers to describe management plans if the ecological classification is uncertain. The numeric values associated with plant community types could help to quantify the uncertainty and guide sampling design for the future, thus helping in the refinement of management plans.

Finally, the detailed information about potential plant community types helps in specifying the differences in classification between the experts and the computer. The numeric values can be used to determine the degree of such differences.

Advantages and Disadvantages of FuzzyTECH

The overwhelming advantage of the FuzzyTECH software package (Inform Software Corporation 2001) was its user-friendly approach. Little experience in programming is needed to use it, and the program runs efficiently even on computers with a processor speed of 233 MHz and 64 MB of RAM. A major limitation of FuzzyTECH for plant community classification is the maximum number of possible output variables for one program (32). This limited the number of plant communities that could be classified with one program. It was for this reason that the pilot study reported here focused on the forested portion of the Montane Natural Subregion of west-central Alberta. If the classification of all ecosites of Alberta were to be computerized, there would be a need to define several broad divisions, and then write a fuzzy logic program for each one.

It was often tedious to generate the rules for output variables. For example, one rule block could potentially have 885 735 rules; however, this task can be simplified by introducing intermediate rule blocks, for example, to address the moisture and nutrient regimes for one ecosite. The intermediate variable generated can then be used in a rule block with the plant species data to define plant community types from that ecosite.

Other limitations of the FuzzyTECH software were the limit on the total number of input, output, and intermediate variables (255), and the limit on the number of characters for terms used to describe the variables (16 characters [letters, numbers, or underscore]); however, these restrictions did not affect the efficiency of our program.

ACKNOWLEDGMENTS

We thank J.H. Archibald and K. Bennett for providing Ecological Site Information System data, and H. Hans for his expertise in formatting the data files used by our program. We are grateful to D.

Allan, M. McLaughlan, J. Stewart and D. Pluth for reviewing the manuscript and providing insights on the final document.

LITERATURE CITED

- Bare, B.B.; Mendoza, G.A. 1988. A soft optimization approach to forest land management planning. *Can. J. For. Res.* 18:545-552.
- Beckingham, J.D.; Corns, I.G.W.; Archibald, J.H. 1996. Field guide to ecosites of west-central Alberta. Nat. Resour. Can., Can. For. Serv., Northwest Reg., North. For. Cent., Edmonton, AB. Spec. Rep. 9.
- Corns, I.G.W.; Annas, R.M. 1986. Field guide to forest ecosystems of west-central Alberta. Can. For. Serv., North. For. Cent., Edmonton, AB.
- Ecological Stratification Working Group. 1995. A national ecological framework for Canada. Agric. Agri-Food Can., Ottawa/Hull. Report and national map at 1:7.5 million scale.
- Inform Software Corporation. 2001. FuzzyTECH professional edition. Version 5.52a. Chicago, Ill. Computer Program.
- Mamdani, E. 1975. An experiment in linguistic synthesis with a fuzzy logic controller. *Int. J. Man-Mach. Stud.* 7:1-13.
- Meidinger, D.; Enns, B.; Banner, A.; Jones, C.; Reed, S. 2000. EcoGen—a model for predictive ecosystem mapping. *EcoNote* [serial on-line] 2000-1:1-5. Accessed 15 June 2002.
<<http://www.for.gov.bc.ca/research/ecogen/downloads/econt01.pdf>>.
- Mulder, J.A.; Corns, I.G.W. 1993. A decision support system for predicting and consolidation of ecosystems from existing map data and classification system. Pages 153-159 in *Proceedings of the 7th Annual Symposium on Geographic Information Systems in Forestry, Environmental and Natural Resources Management, February 15-18, 1993, Vancouver, B.C.* Vol. 1. Polaris Conferences, Vancouver, B.C.
- Payandeh, B.; Dukes, D.; Baldwin, K. 1995. Users' guide to FEXPERT: forest ecosystem classification made easy. Nat. Resour. Can., Can. For. Serv., Great Lakes For. Cent., Sault Ste. Marie, ON. Inf. Rep. U-X-443.
- Ponomarenko, S.; Alvo, R. 2001. Perspectives on developing a Canadian classification of ecological communities. Nat. Resour. Can., Can. For. Serv., Ottawa, ON. Inf. Rep. ST-X-18E.
- Roberts, D.W. 1989. Fuzzy systems vegetation theory. *Vegetatio* 83:71-80.
- Roberts, D.W. 1996a. Modelling forest dynamics with vital attributes and fuzzy systems theory. *Ecol. Model.* 90:161-173.
- Roberts, D.W. 1996b. Landscape vegetation modelling with vital attributes and fuzzy systems theory. *Ecol. Model.* 90:175-184.
- Sowell, T. 1998. Fuzzy logic for "just plain folks". Plug in to the systems control, financial and emotional success genius born in you. Tesco Publishing Co., Lubbock, TX.
- Von Altrock, C. 1995. Fuzzy logic and NeuroFuzzy applications explained. Prentice Hall PTR, Prentice-Hall Inc., Toronto, ON.
- Von Altrock, C. 1997. Fuzzy logic and NeuroFuzzy applications in business and finance. Prentice Hall PTR, Prentice-Hall Inc., Toronto, ON.

APPENDIX 1 DESCRIPTION OF INPUT VARIABLES

Variable names	Unit	Value of variable			Linguistic terms
		Minimum	Maximum	Default	
arctuva betupap cornsto elyminn equispp heralan junispp ledugro picegla picemar pinucon popubal poputre pseumen rosaaci salispp shepcan	percent cover	0	100	50	very low low medium high
moisture regime	class	0	10	5	very xeric xeric subxeric submesic mesic subhygric hygric subhydric hydric
nutrient regime	class	0	6	3	very poor poor medium rich very rich
shrub	percent cover	0	100	0	low high

APPENDIX 2

DESCRIPTION OF OUTPUT VARIABLES

Variable names	Unit	Value of variable		Default	Linguistic terms
		Minimum	Maximum		
Aw_bearbuff_rye	class	0	100	0	very_low low medium high very_high
Aw_buff_rye					
Aw_rose_rye					
Aw_sask_rye					
AwSwPl_bear_rye					
AwSwPl_buff_rye					
AwSwPl_rose_rye					
Fd_bearbuff_rye					
Fd_buff_rye					
Fd_wildrye_fmoss					
PbAw_cowparsnip					
PbAw_dogwood					
PbAw_horsetail					
PbSw_dogwood					
Pl_bearbuff_rye					
Pl_buff_rye					
Pl_fmoss					
Pl_wildrye					
Sb_labte_sed_gmo					
Sb_willow_sed_gm					
Sw_bearjun_fmoss					
Sw_buff_rye_fmoss					
Sw_fmoss_wfmoss					
Sw_horsetail					
Sw_wildrye_fmoss					
Sw_willow					

APPENDIX 3

DESCRIPTION OF INTERMEDIATE VARIABLES

Variable names	Unit	Value of variable			Linguistic terms
		Minimum	Maximum	Default	
AwSwP1	class	0	100	0	very_low
bear_jun					low
Pb_Aw					medium
PbBwAw					high
wildrye1					very_high
wildrye					

APPENDIX 4

**RULE BLOCK FOR THE OUTPUT VARIABLE Aw_rose_rye, WHICH
REPRESENTS THE PLANT COMMUNITY TYPE
ASPEN/PRICKLY ROSE/HAIRY WILD RYE**

Aw_Pb^a	rosaaci	If shrub	wildrye1^a	Then Aw_rose_rye
very_low	low	low	very_low	very_low
very_low	medium	low	very_low	very_low
very_low	high	low	very_low	very_low
low	very_low	low	very_low	very_low
low	low	low	very_low	very_low
low	medium	low	very_low	very_low
low	high	low	very_low	very_low
medium	very_low	low	very_low	very_low
medium	low	low	very_low	very_low
medium	medium	low	very_low	very_low
medium	high	low	very_low	very_low
high	very_low	low	very_low	very_low
high	low	low	very_low	very_low
high	medium	low	very_low	very_low
high	high	low	very_low	very_low
very_low	very_low	low	very_low	very_low
very_low	NA ^b	low	low	very_low
low	NA	low	low	very_low
medium	NA	low	low	very_low
high	NA	low	low	very_low
very_low	NA	low	medium	very_low
low	NA	low	medium	very_low
medium	NA	low	medium	very_low
high	NA	low	medium	very_low
very_low	NA	low	high	very_low
low	NA	low	high	very_low
medium	NA	low	high	very_low
high	NA	low	high	very_low
very_low	NA	high	very_low	very_low
low	NA	high	very_low	very_low
medium	NA	high	very_low	very_low
high	NA	high	very_low	very_low
medium	medium	high	low	low
medium	high	high	low	low
high	high	high	low	low
high	medium	high	low	low
very_low	NA	high	low	very_low

Appendix 4. Continued

Aw_Pb ^a	rosaaci	If		Then Aw_rose_rye
		shrub	wildrye1 ^a	
low	NA	high	low	very_low
medium	very_low	high	low	very_low
medium	low	high	low	very_low
high	low	high	low	very_low
high	very_low	high	low	very_low
medium	medium	high	medium	medium
medium	high	high	medium	medium
high	medium	high	medium	high
high	high	high	medium	very_high
high	low	high	medium	low
medium	low	high	medium	low
low	medium	high	medium	low
low	high	high	medium	low
very_low	NA	high	medium	very_low
low	very_low	high	medium	very_low
low	low	high	medium	very_low
medium	very_low	high	medium	very_low
high	very_low	high	medium	very_low
very_low	NA	high	high	very_low
low	very_low	high	high	very_low
low	low	high	high	very_low
low	medium	high	high	low
low	high	high	high	low
medium	high	high	high	very_high
high	high	high	high	very_high
medium	medium	high	high	high
high	medium	high	high	high
medium	low	high	high	low
high	low	high	high	low
medium	very_low	high	high	very_low
high	very_low	high	high	very_low

^aAw_Pb and wildrye1 are intermediate variables used in this rule block. See Appendixes 5 and 6 for the rule blocks for these intermediate variables.

^bNA = not applicable; the rule block can occur independent of rosaaci (prickly rose percent cover).

APPENDIX 5

RULE BLOCK FOR THE INTERMEDIATE VARIABLE wildrye1

elyminn	If moisture_regime	nutrient_regime	Then wildrye1
high	Submesic	medium	high
high	mesic	medium	high
high	subhygric	medium	high
high	submesic	rich	high
high	mesic	rich	high
high	subhygric	rich	high
very_low	NA ^a	very_poor	very_low
low	NA	very_poor	very_low
low	subhydric	medium	very_low
low	hydric	medium	very_low
low	hydric	rich	very_low
low	subhydric	rich	very_low
low	very_xeric	medium	very_low
low	xeric	medium	very_low
low	xeric	rich	very_low
low	very_xeric	rich	very_low
medium	NA	very_poor	very_low
medium	very_xeric	medium	very_low
medium	xeric	medium	very_low
medium	xeric	rich	very_low
medium	very_xeric	rich	very_low
medium	subhydric	medium	very_low
medium	hydric	medium	very_low
medium	hydric	rich	very_low
medium	subhydric	rich	very_low
high	NA	very_poor	very_low
high	subhydric	poor	very_low
high	hydric	poor	very_low
high	hydric	medium	very_low
high	subhydric	medium	very_low
high	subhydric	rich	very_low
high	hydric	rich	very_low
high	hydric	very_rich	very_low
high	subhydric	very_rich	very_low
high	xeric	very_rich	very_low
high	very_xeric	very_rich	very_low
high	very_xeric	poor	very_low
high	xeric	poor	very_low
high	very_xeric	medium	very_low

Appendix 5. Continued

elyminn	If		Then wildrye1
	moisture_regime	nutrient_regime	
high	xeric	medium	very_low
high	very_xeric	rich	very_low
high	xeric	rich	very_low
high	subxeric	poor	very_low
high	subxeric	very_rich	very_low
high	hygric	very_rich	very_low
high	hygric	poor	very_low
medium	very_xeric	poor	very_low
medium	xeric	poor	very_low
medium	subxeric	poor	very_low
medium	very_xeric	very_rich	very_low
medium	xeric	very_rich	very_low
medium	subxeric	very_rich	very_low
medium	hygric	very_rich	very_low
medium	subhydric	very_rich	very_low
medium	hydric	very_rich	very_low
medium	hygric	poor	very_low
medium	subhydric	poor	very_low
medium	hydric	poor	very_low
low	very_xeric	poor	very_low
low	xeric	poor	very_low
low	subxeric	poor	very_low
low	very_xeric	very_rich	very_low
low	xeric	very_rich	very_low
low	subxeric	very_rich	very_low
low	hygric	very_rich	very_low
low	subhydric	very_rich	very_low
low	hydric	very_rich	very_low
low	hydric	poor	very_low
low	subhydric	poor	very_low
low	hygric	poor	very_low
very_low	very_xeric	medium	very_low
very_low	xeric	medium	very_low
very_low	xeric	rich	very_low
very_low	very_xeric	rich	very_low
very_low	subhydric	medium	very_low
very_low	hydric	medium	very_low
very_low	hydric	rich	very_low
very_low	subhydric	rich	very_low
very_low	very_xeric	poor	very_low
very_low	xeric	poor	very_low
very_low	subxeric	poor	very_low

Appendix 5. Continued

elyminn	If moisture_regime	nutrient_regime	Then wildrye1
very_low	subxeric	very_rich	very_low
very_low	xeric	very_rich	very_low
very_low	very_xeric	very_rich	very_low
very_low	hygric	very_rich	very_low
very_low	subhydric	very_rich	very_low
very_low	hydric	very_rich	very_low
very_low	hygric	poor	very_low
very_low	hydric	poor	very_low
very_low	subhydric	poor	very_low
medium	submesic	medium	high
medium	mesic	medium	high
medium	subhygric	medium	high
medium	subhygric	rich	high
medium	mesic	rich	high
medium	submesic	rich	high
very_low	submesic	poor	low
very_low	mesic	poor	low
very_low	subhygric	poor	low
very_low	hygric	medium	low
very_low	hygric	rich	low
very_low	subhygric	very_rich	low
very_low	mesic	very_rich	low
very_low	submesic	very_rich	low
very_low	subxeric	rich	low
very_low	subxeric	medium	low
very_low	submesic	medium	medium
very_low	mesic	medium	medium
very_low	subhygric	medium	medium
very_low	subhygric	rich	medium
very_low	mesic	rich	medium
very_low	submesic	rich	medium
low	hygric	medium	low
low	hygric	rich	low
low	subhygric	very_rich	low
low	mesic	very_rich	low
low	submesic	very_rich	low
low	subxeric	rich	low
low	subxeric	medium	low
low	submesic	poor	low
low	mesic	poor	low
low	subhygric	poor	low
low	submesic	medium	high

Appendix 5. Continued

elyminn	If		Then wildrye1
	moisture_regime	nutrient_regime	
low	mesic	medium	high
low	subhygric	medium	high
low	subhygric	rich	high
low	mesic	rich	high
low	submesic	rich	high
medium	submesic	poor	low
medium	mesic	poor	low
medium	subhygric	poor	low
medium	hygric	medium	low
medium	hygric	rich	low
medium	subhygric	very_rich	low
medium	mesic	very_rich	low
medium	subxeric	rich	low
medium	subxeric	medium	low
medium	submesic	very_rich	low
high	submesic	poor	low
high	mesic	poor	low
high	subhygric	poor	low
high	hygric	medium	low
high	hygric	rich	low
high	subhygric	very_rich	low
high	mesic	very_rich	low
high	submesic	very_rich	low
high	subxeric	rich	Low
high	subxeric	medium	Low

*NA = not applicable; the rule block can occur independent of moisture regime.

APPENDIX 6

RULE BLOCK FOR THE INTERMEDIATE VARIABLE Aw_Pb

If		Then
popubal	poputre	Aw_Pb
high	high	high
medium	high	high
low	high	high
very_low	high	high
high	medium	high
high	low	high
high	very_low	high
medium	very_low	medium
medium	low	medium
medium	medium	high
low	medium	medium
very_low	medium	medium
low	low	low
low	very_low	low
very_low	low	low
very_low	very_low	very_low